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Energetic characterization of near surface windfield in Hungary

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Abstract

The article, which is a segment of a complex wind energy examination, uses statistical methods to analyse the daily specific wind power of a month in the period between 1991 and 2000 measured on seven Hungarian meteorological stations. The properties of monthly average specific wind power can be examined by definite integral (area under the curve) of an approximation function fitted on the hourly average of the cubes of wind speed. We only discuss certain properties of the approximation function here that may offer implications about the daily course of wind energy. Thus we outline a statistical stochastic model, which could be utilized by energetic systems management in producing electricity from wind energy.

Keywords: Average specific wind power; Trigonometric polynomials; Relative amount of approximation; Suddenness of the approximation function

Contents

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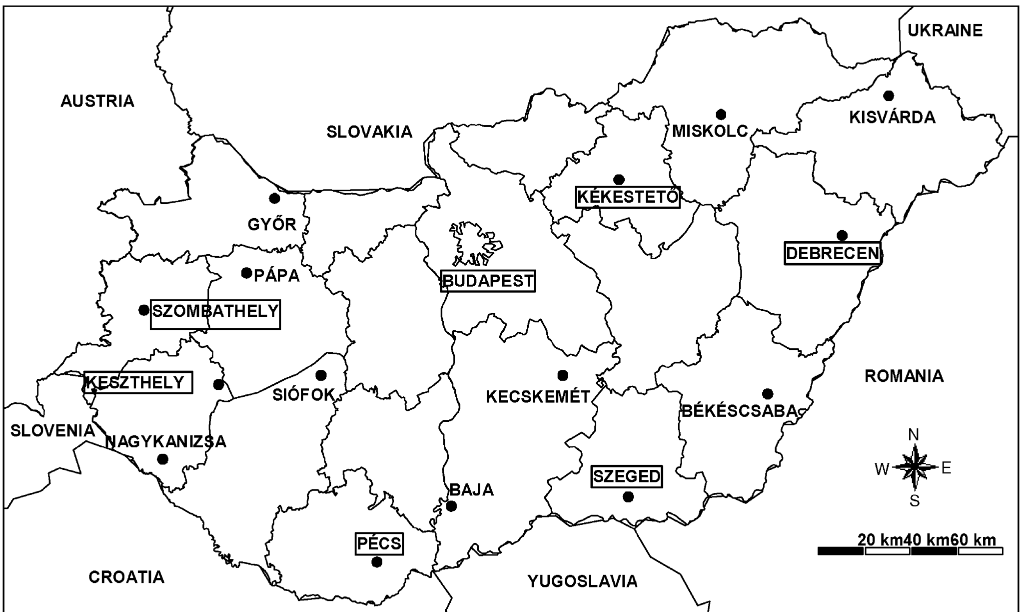
1. Objective, database and methods

The article discusses a segment of a complex examination whose objective is to reveal the interdependence of parameters in wind energetic in order to outline a statistical stochastic model that may be useful in everyday wind energy utilization.

The hourly wind speed data for ten Hungarian meteorological observatories in the period from 1991 to 2000 required for the energetic examination, and the 10 min tower measurement wind speed data in Paks in the years 2000 and 2001 were provided by the Hungarian National Meteorological Service. Fig. 1 shows the geographical locations of the stations. The weather stations in Debrecen, Békéscsaba, Miskolc and Győr were relocated



Observatory	φ	λ	h (m)	h_a (m)
			1991-2000	
Szombathely	47°16’	16°38’	219	9
Keszthely	46°46’	17°14’	117	15
Pécs	46°00’	18°14’	201	10
Budapest-L.	47°27’	19°13’	130	12
Szeged	46°15’	20°06’	83	9
Debrecen	47°30’	21°38’	111	10
Kékestető	47°52’	20°01’	1011	26

Fig. 1. Geographical locations and exact geographical coordinates (φ: latitude, λ: longitude, h: elevation) of the observatories and anemometer altitudes (h_a) of the meteorological observatories comprising the database.

(at least once) in the period from 1971 to 2000 of the comprehensive study not restricted to wind speed examination. The relocation did not caused substantial change in the latitudes or longitudes of any stations concerned, but it significantly increased the elevation in Miskolc and the anemometer height in Békéscsaba. Both heights changed minimally in Győr. In Debrecen, the station relocation caused no significant changes in basic wind statistics as one of our earlier studies showed [1], unlike to Győr where it did which can be shown by a simple homogeneity test of the wind data time series. The reason for this is probably the different environment at the new location. Hence we only used station data whose monthly data series can be regarded homogeneous in the period from January 1971 to December 2001. Thus anemometric conditions can be considered constant in the following stations: Debrecen, Szeged, Budapest, Pécs, Keszthely, Szombathely and Kékestető. Fig. 1 shows the exact geographical coordinates and the altitude of the wind-gauge above ground level for the observatories above, too.

Properties of the monthly average specific wind power can be described with the definite integral (area under the curve) of proportional trigonometric polynomial matching the hourly averages of the cubes of wind speeds. We define an index number to approximate the above function, and we analyse its spatial variation. We will draw our conclusions concerning the daily course of wind energy from the discussion of the suddenness in the daily and 12-h waves of the approximation function.

2. Determining monthly average specific wind power with an approximation function

Specific wind power is defined as the kinetic energy of the air mass passing through a unit of vertical area in a unit of time. We can calculate it at any given time with the formula

$$P_{\mathrm{f}} = \frac{\rho}{2} v^3, \tag{1}$$

where v is the speed of wind, ρ is air density, its unit of measurement is $\mathrm{W\,m^{-2}}$. There are two options to determine the specific wind power of an extended period: either we substitute the average speed during the period for v or we add wind power values defined at individual discreet points in time within the period in question.

The second option is obviously more realistic. It is problematic, though, that in this case the sum depends on the number of measurement times, as we will get different values for the sum if we calculate them from wind speeds measured in every hour or in every 10 min or at the so called terminal points each day. Though averaging might reduce, it cannot entirely eliminate the dependence on the number of measurement points. Daily average specific wind power itself, which in fact means a specific wind power falling on a single measurement time on the average, depends on the number of reference points and on what times of the day we use for measurement as well.

There is a theoretical solution to eliminate this dependence: if multiply the area under the curve of the function describing daily variation in the cubes of wind speeds with $\rho/2$, we will obtain the exact value of all the daily specific wind power. We, of course, must used numerical integration, as the necessary function is not analytical on a usual day. We may attempt to determine the average specific wind power falling on a period consisting of days, for instance month, season or year, by the help of an appropriately selected approximation function.

2.1. The method

The wind speeds at discreet measurement times for each day of a specific period are given. We eliminate the dependence on the number of measurement times if we can find a continuous approximation function and we can determine the area under its curve with analytic integration.

Specific wind power falling on a day of a period on average is defined as half of the air density multiplied by the area under a function curve that approximates the daily course of the averages of wind speed cubes by measurement time.

The approximation function is

$$f_2(x) = a_0 + \sum_{m=1}^{2}\left(a_m \cos\frac{2\pi mx}{N} + b_m \sin\frac{2\pi mx}{N}\right). \tag{2}$$

It is the first two member of a Fourier series which consists of trigonometric polynomials where N is the number of daily measurement times and $x = 0, 1, 2, \ldots, N$-1. The goodness of approximation or fitting can be described by the so-called residual variance:

$$s_m^2 = s_{m-1}^2 - 0.5A_m^2, \tag{3}$$

where $s_0^2 = s_n^2$, thus the square of deviation is

$$A_m = (a_m^2 + b_m^2)^{1/2}, \tag{4}$$

which is the amplitude of the wave m [2]. It is obvious, though, that s_m^2 depends on the size of the data, and thus it is not usable for comparison in our case. For that purpose we use the parameter, which determines the relative amount of approximation:

$$s_{0m} = \frac{s_0^2 - s_m^2}{s_0^2}, \tag{5}$$

which might be considered value independent, thus it does not depends on the magnitude of wind speeds, therefore it needs not to be corrected for anemometer altitude. s_m^2 values obviously lessen as the number of approximating polynomials increases. Let us assume the opposite when $s_m^2 \approx s_0^2$, i.e., $s_{0m} \approx 0$. If, on the other hand, approximation with $f_2(x)$ is "perfect", then $s_m^2 \approx 0$, i.e., $s_{0m} \approx 1$. The closer s_{0m} falls to 1 the better fit the approximation function shows [1,3].

The primitive of function (2) is

$$F_2(x) = a_0 x + \sum_{m=1}^{2}\left(\frac{a_m}{\alpha_m}\sin \alpha_m x - \frac{b_m}{\alpha_m}\cos \alpha_m x\right), \tag{6}$$

where $\alpha_m = (2\pi m)/N$. Consequently, if we use the time series of the averages of wind speed cubes by measurement times to determine coefficients a_m and b_m, the average specific wind power falling on a day in the period is

$$P_{\text{fmd}} = \frac{\rho}{2}[F_2(N-1) - F_2(0)],$$

where

$$T_{\text{ga}} = F_2(N-1) - F_2(0) \tag{7}$$

is the area under the curve. The definite integral gives the area under the curve in units determined by values of x. That depends on how many measurement times we chose to specify in a day. We must take that fact in consideration when we compare calculated values.

We developed the above method to determine the daily average specific wind power based on hourly measurement data [1,3]. First, we demonstrate below using the 10 min tower measurement data in Paks ($N = 144$) that our method is in fact capable to eliminate dependence on the number of measurement times. Table 1 contains the statistical properties ($[v]$, s_v, $[v^3]_1$) derived from 50 m measurement data, the goodness-of-fit (s_{02}) and the areas under the curve ($F_2(N\text{-}1)\text{-}F_2(0)$) for each month in 2000 and 2001 using 10 min ($N = 144$) and selected hourly ($N = 24$) measures. The last column in the table gives the deviation of the areas under the curve in percentage of the hourly values. The areas calculated from the 10 min data are only 1–7%, the average is 3.2%, greater than the results calculated from the hourly data with the single exception of July 2001.

Next, we will discuss time series of average wind power falling on a day of a month, i.e., we apply the method described above for all the months in the period between 1991 and 2000 at all seven stations.

Table 1
Averages of monthly average wind speeds calculated from hourly and 10 min measurements ($[v]$), of standard deviations (s_v) and of cubes of wind speeds ($[v^3]_1$) by measurement times, as well as the goodness of approximation by a trigonometric polynomials (s_{02}), area of the approximation function under its curve (T_{ga24} és T_{ga144}), that is the daily average of the cubes of wind speeds), and the difference of the latter two (in percentage) in Paks at 50 m

		From the hourly values					From the 10 min values					
Year	Months	$[v]$ (m/s)	s_v (m/s)	$[v^3]_1$ (m³/s³)	s_{02}	T_{ga24} (m³/s³)	$[v]$ (m/s)	s_v (m/s)	$[v^3]_1$ (m³/s³)	s_{02}	T_{ga144} (m³/s³)	%
2000	1	4.13	2.71	186.5	0.37	4239.5	4.13	2.67	182.0	0.35	4329.6	2.1
	2	4.40	2.18	154.4	0.71	3552.2	4.40	2.18	154.1	0.68	3672.7	3.4
	3	4.96	2.26	206.7	0.89	4829.7	4.94	2.29	208.4	0.91	4979.5	3.1
	4	4.21	2.23	149.5	0.77	3475.9	4.19	2.26	151.0	0.82	3604.4	3.7
	5	3.27	1.73	68.6	0.55	1574.6	3.26	1.75	69.3	0.58	1651.2	4.9
	6	3.76	2.05	108.2	0.71	2506.5	3.75	2.03	106.3	0.74	2536.4	1.2
	7	4.73	2.06	169.2	0.92	3943.4	4.69	2.03	164.9	0.91	3939.4	-0.1
	8	3.24	1.68	64.5	0.29	1478.7	3.24	1.68	64.8	0.52	1543.0	4.3
	9	3.22	1.80	70.7	0.46	1617.1	3.19	1.79	69.6	0.51	1655.7	2.4
	10	3.46	1.58	69.3	0.79	1600.1	3.46	1.57	68.6	0.77	1635.9	2.2
	11	3.85	1.75	94.4	0.38	2184.0	3.86	1.74	94.9	0.38	2262.3	3.6
	12	3.17	1.72	63.1	0.58	1449.0	3.19	1.71	63.5	0.61	1512.3	4.4
2001	1	3.79	1.81	94.4	0.86	2185.1	3.79	1.79	93.6	0.88	2232.8	2.2
	2	4.84	2.40	205.2	0.76	4755.2	4.82	2.40	203.3	0.71	4848.5	2.0
	3	4.35	1.78	127.6	0.38	2940.1	4.33	1.78	126.1	0.41	3006.2	2.2
	4	4.38	2.48	177.6	0.90	4127.5	4.36	2.48	176.5	0.86	4213.5	2.1
	5	3.97	1.93	112.1	0.65	2563.4	3.95	1.91	110.5	0.72	2631.9	2.7
	6	4.68	2.46	201.8	0.84	4683.1	4.70	2.45	203.4	0.84	4853.0	3.6
	7	3.77	1.90	97.2	0.67	2253.6	3.78	1.88	96.6	0.74	2306.1	2.3
	8	3.14	1.73	66.0	0.51	1511.8	3.14	1.74	66.3	0.56	1580.4	4.5
	9	3.94	1.92	113.2	0.85	2633.0	3.95	1.98	117.6	0.77	2807.3	6.6
	10	3.06	1.54	51.9	0.67	1195.5	3.09	1.54	53.0	0.73	1263.7	5.7
	11	4.39	2.42	170.4	0.79	3931.8	4.42	2.45	175.3	0.68	4180.1	6.3
	12	3.47	1.88	84.2	0.64	1945.3	3.47	1.85	82.6	0.57	1968.9	1.2

2.2. Fit of the approximation function

First, we analyse the spatial variation of the dimension defined by formula (5). Table 2 contains the most important statistical properties of this parameter. The averages show that the approximation was the best in Szeged and Debrecen while the worst in Keszthely and Pécs. The variability of the parameter, which is indicated by the range, i.e., the difference between the extremities or by the variation coefficient appears in reverse sequence of the previous series in general. Maximums mainly occur in spring and summer months but never in autumn or winter, while minimums appear only in the winter. We also calculated the correlation coefficients between s_{02} and $[v]$, since one might assume a dependence of the goodness-of-fit on speed. The respective threshold values for significance levels of 0.05 and 0.10 are $|r_{0.05}|\approx 0.1793$, and $|r_{0.10}|\approx 0{,}1509$ assuming the element number to be $n\approx 120$. Next to last row in the table shows that the stochastic relationship exists everywhere at least on the 0.05 significance level, except at Kékestető.

The last row of the table lists the relative frequency in percentage of those parameter values that exceed the average. It is the lowest at Szombathely and the highest at Kékestető a frequency well beyond 50%.

There is no observable annual cycle in the appearance of elements exceeding the average due to the small number of cases. If, however, all seven stations treated together, we find that the values in March and April as well as those in September and October are beyond 10%, altogether representing 43.7%. It is remarkable that we found minimums very close to 0 within the extreme values. The absolute minimum is 0.03, which occurred in December 2000 in Keszthely. The absolute maximum is 0.98, which occurred in August 1994 in Debrecen. Fig. 2 shows these cases, which made it feasible to decide the suddenness of both the daily and the 12 h waves.

2.3. Suddenness of the approximation function

Fourier analysis calls the expected values of amplitudes expectancy (E):

$$E = s_n\sqrt{\frac{\pi}{N}}. \tag{8}$$

To decide whether the period N/m of the m wave is random or real the relation between A_m amplitude and E expectancy is used. In case of great enough A_m/E, the probability (p)

Table 2
Essential statistical properties of the parameter describing the goodness of approximation (s_{02})

	Debrecen	Szeged	Budapest	Pécs	Keszthely	Szombathely	Kékestetö
Mean	0.77	0.79	0.74	0.68	0.71	0.76	0.76
St. dev.	0.17	0.15	0.18	0.21	0.21	0.17	0.16
Var. coeff.	0.22	0.19	0.24	0.32	0.30	0.22	0.21
Max.	0.98	0.96	0.95	0.96	0.95	0.96	0.97
Min.	0.13	0.30	0.10	0.07	0.03	0.13	0.13
Range	0.85	0.66	0.85	0.89	0.92	0.83	0.84
Correlation coeff.	0.2042	0.2408	0.2198	0.2086	0.1863	0.2960	0.1326
> %	63.3	62.5	60.8	61.7	61.0	59.3	64.2

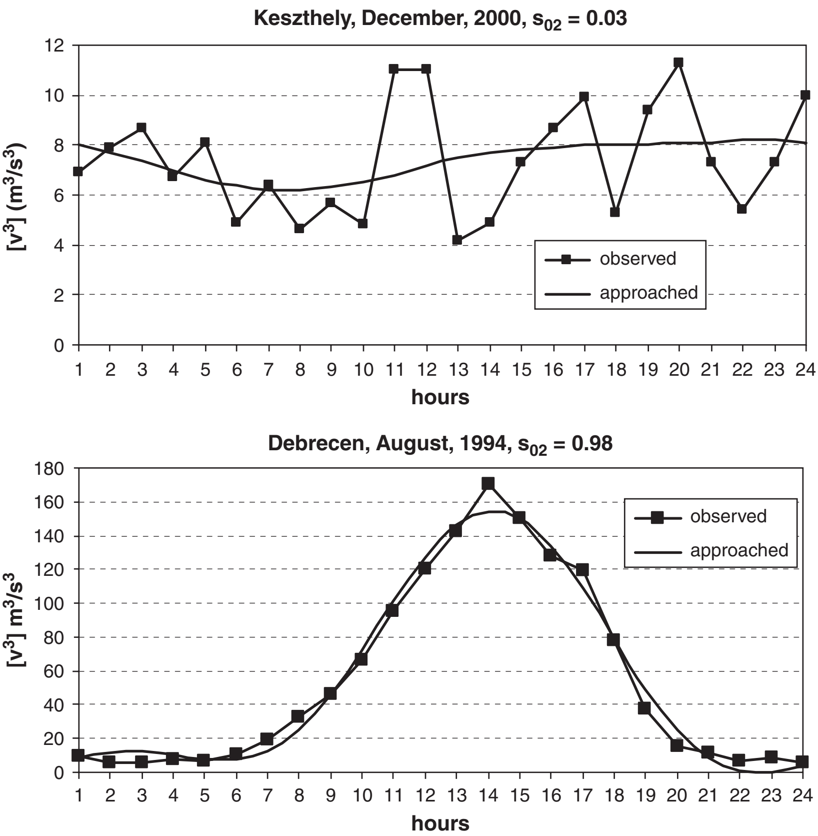


Fig. 2. Worst and best approximation of the hourly average wind speed cubes.

of random order in the data is low, thus it can be considered real statistically. In general, $A_m/E>2$ is acceptable ($p = 0.05$), but in the periodic analysis of time series of meteorological data the wave is considered real when $A_m/E>1.5$ ($p = 0.17$) is met [4].

Table 3 shows that the daily wave must not be considered random in 80–90% of the cases at the significance level of 0.05 and in 89.2–97.5% of the cases at the 0.17 significance level, as it was expected. More interesting is the suddenness of the 12 h wave where the ranges in the table are 11.7–25% and 29.2–57.5%, respectively.

Let us take a closer look at the annual variation of the latter non-random waves at 0.17 significance level. We will examine the monthly distribution of those cases where $A_m/E>1.5$ according to station types. We will distinguish lowland (Debrecen, Szeged and Budapest), and non-lowland stations (Pécs, Keszthely and Szombathely) with and without Kékestető. Fig. 3 shows the frequency of fulfilled conditions in percentage by station types and in all stations together. It is clear that the condition is not met in July at the lowland stations where the frequency raises above 10% in the autumn and winter months in addition to March. The maximum is in October while the secondary maximum occurs in February. The months for the annual maximum and secondary maximum are the same in the case of non-lowland stations, but the value of the primary maximum reduces in

Table 3
Percentages of the reality of the daily and the 12 h waves at significance levels of 0.05 ($A_k/E>2$) and 0.17 ($A_k/E>1.5$)

%	Debrecen	Szeged	Budapest	Pécs	Keszthely	Szombat-hely	Kékestetö
$A_1/E>3$	*74.2*	*68.3*	*62.5*	*45.8*	*56.7*	*65.8*	*65.0*
$A_1/E>2$	95.0	92.5	95.0	80.0	88.3	94.2	91.7
$A_1/E>1.5$	97.5	95.8	95.8	89.2	92.5	97.5	95.0
$A_2/E>2$	12.5	24.2	11.7	25.0	12.5	17.5	17.5
$A_2/E>1.5$	40.0	50.0	38.3	57.5	36.7	40.8	29.2

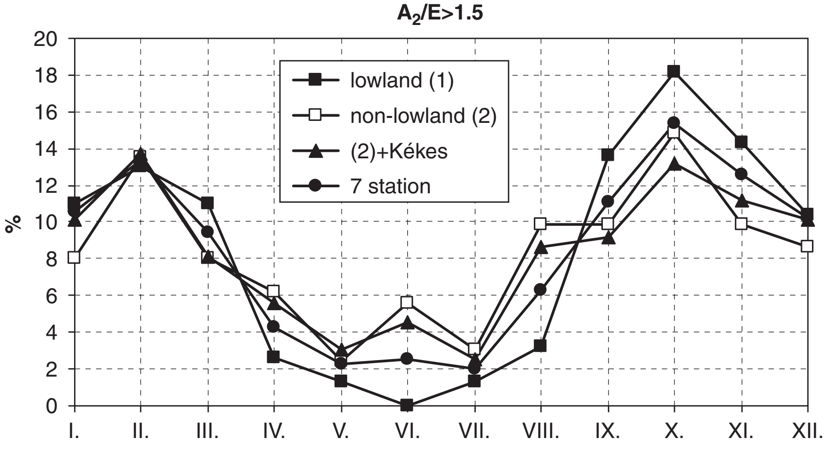


Fig. 3. Monthly frequencies of the reality of the 12 h wave ($p = 0.17$).

favour for June when an approximately 6% high tertiary maximum occurs. The maximums remain the same if Kékestető is included, but the months of the primary and secondary maximums are transposed. We may state that the curve shows the characteristics of the non-lowland stations when all seven stations examined together.

The 12-h wave of trigonometric polynomials fitted monthly on the cubes of the hourly average wind speeds shows suddenness mainly in the late spring and summer months at 0.17 significance level, while the frequency of its probable reality increases in the winter, early spring and autumn months, i.e., for the major part of the year. Thus we may expect significant daily alterations of wind energy, its morning and afternoon minimums as well as its daytime and night maximums (the other way round in case of Kékestető). There is no circadian change of wind energy in those cases where the 12 h wave is random, for they are dominated by the daily cycle with a single maximum around midday. Figs. 4 and 5 illustrate the above where the hourly average of measured cubes of wind speeds appear by months corresponding to extreme A_m/E ratios together with approximate values of waves 1 and 2. Fig. 5 clearly shows that at minimal A_m/E ratio the two waves practically coincide, i.e., the approximation does not significantly increase including the second random wave.

Temporal alternation of potential wind power is extremely inconvenient for the system management in electricity production, for the power loss must be made up for from other sources. The greatest daily difference can exceed 80% in Germany [5]. Figs. 6 and 7 show

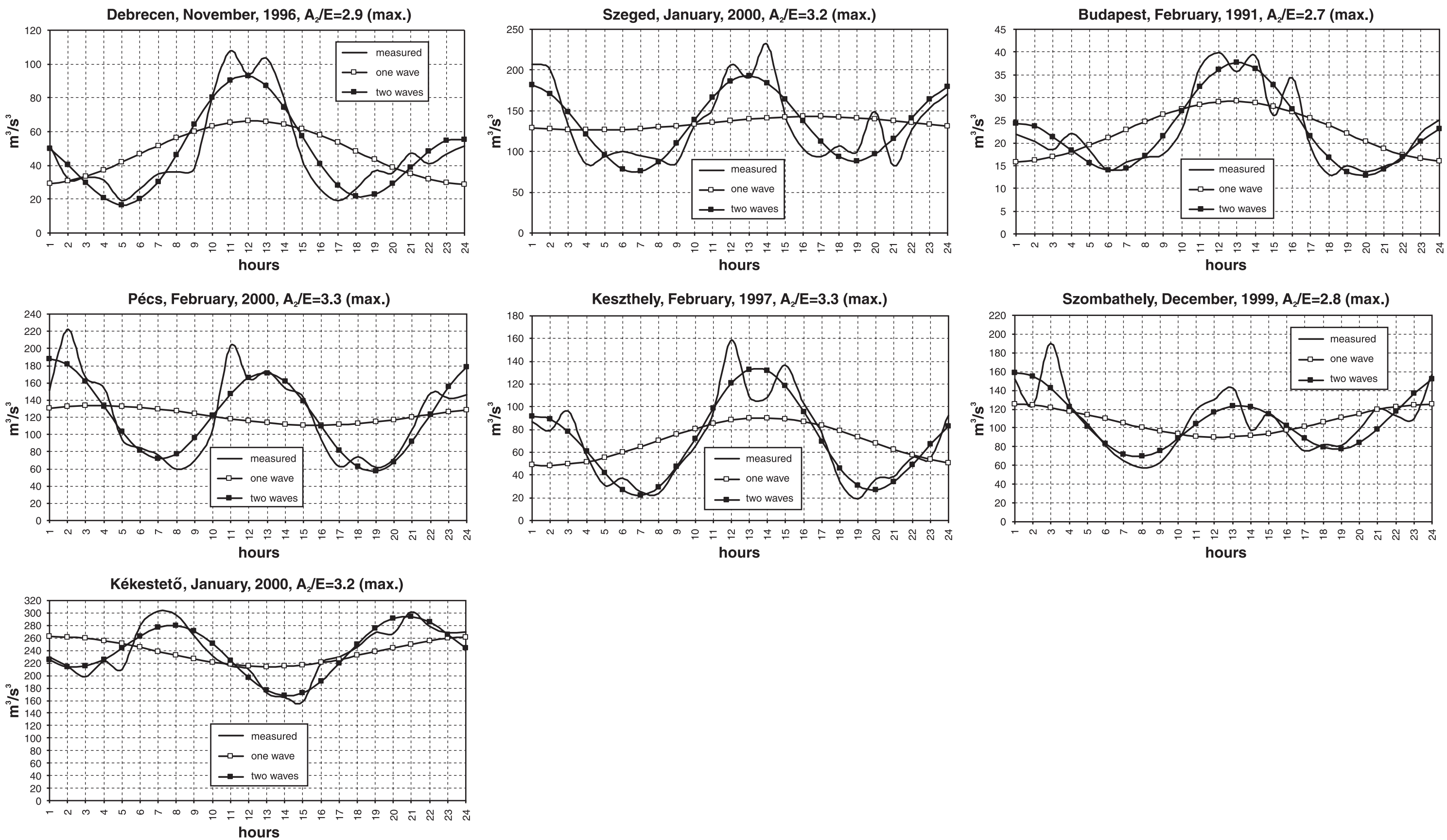


Fig. 4. Approximation with one and two waves of the cubes of hourly average wind speeds in case of very strong second wave (12 h period).

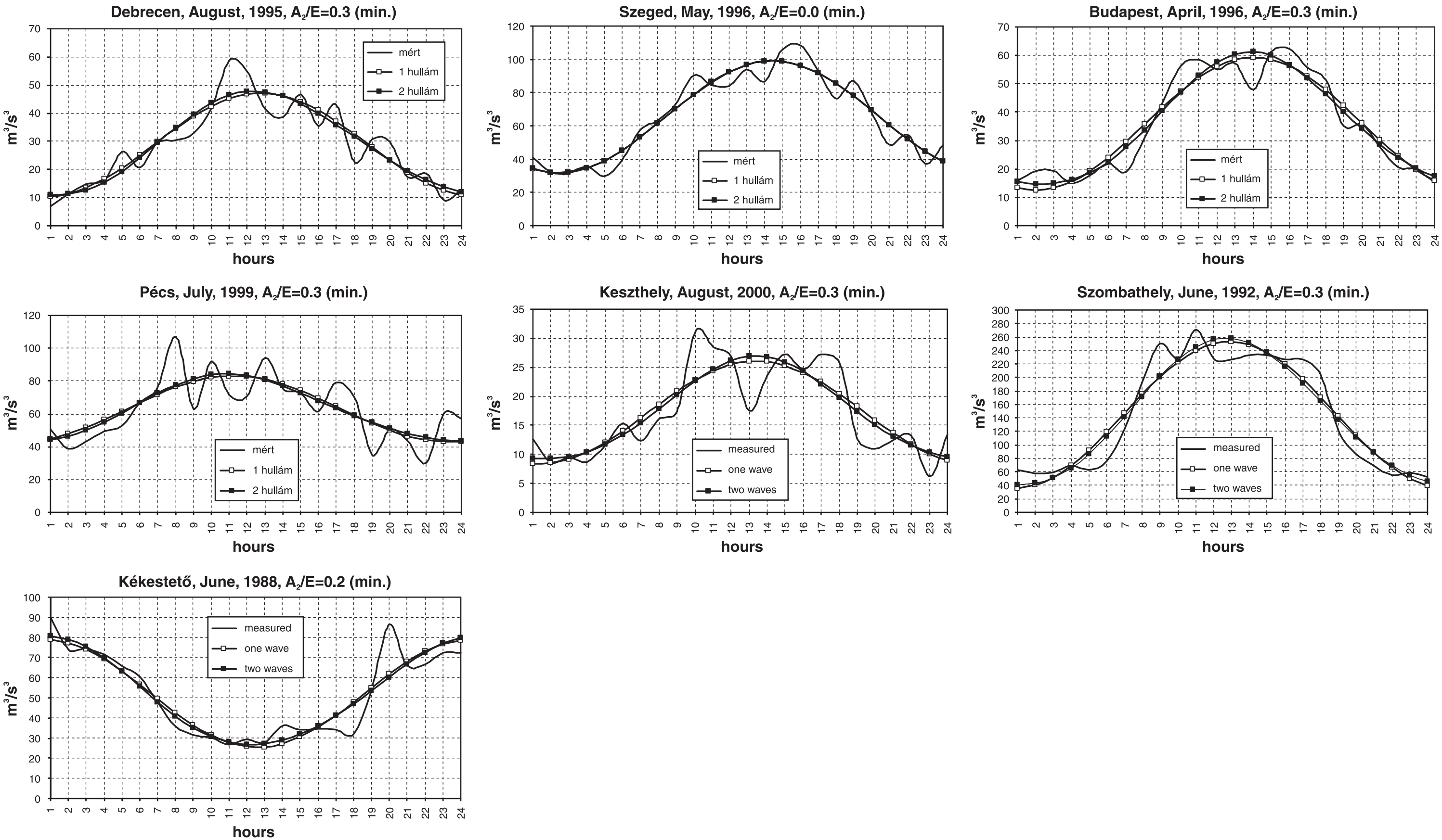


Fig. 5. Approximation with one and two waves of the cubes of hourly average wind speeds in case of very week second wave (12 h period).

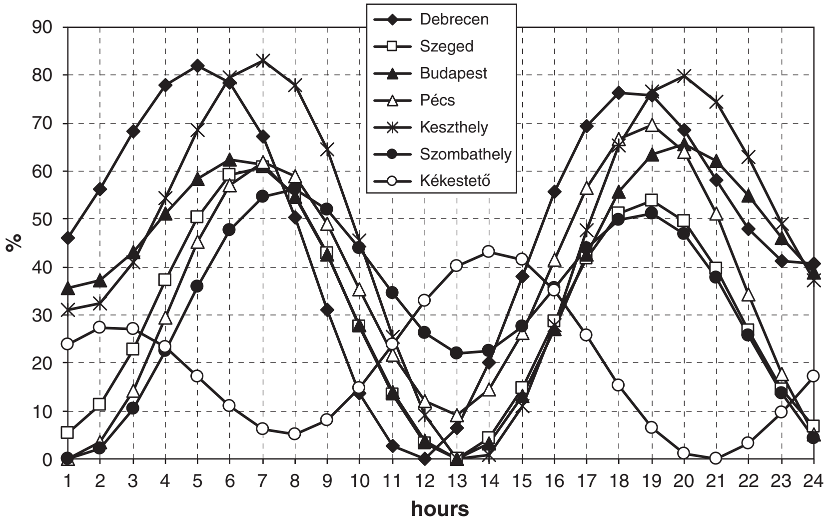


Fig. 6. Deviation of the cubes of hourly average wind speeds from daily maximums in case of real 12 h wave (in the months appearing in Fig. 4).

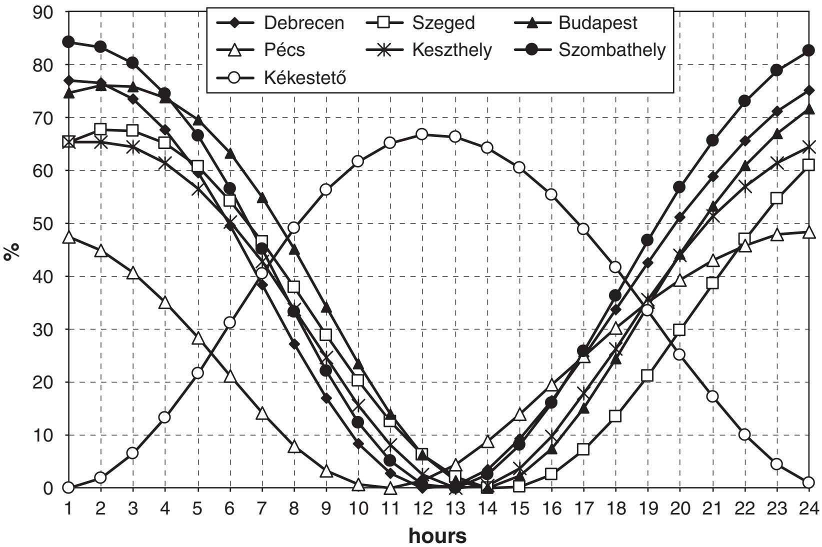


Fig. 7. Deviation of the cubes of hourly average wind speeds from daily maximums in case of random 12 h wave (in the months appearing in Fig. 5).

daily differences in the cases that appear in Figs. 4 and 5, they indicate the deviation of the hourly average wind speed cubes from the daily maximum in percentage based on the approximate data.

As it follows from Fig. 6, if there is a real 12 h wave, the morning and afternoon maximums in Debrecen and Keszthely are approximately 80% and they fall between 60%

and 70% in Budapest and Pécs, while between 50% and 60% in Szombathely and Szeged. The daily difference is lowest in Kékestető where it raises above 40% only in the afternoon. According to Fig. 7 in case of a non-dominant, random 12 h wave the greatest differences from the daily maximums in the night are over 80% in Szombathely, between 70% and 80% in Debrecen and Budapest, between 60% and 70% in Keszthely and Szeged, while between 40% and 50% in Pécs. The differences, of course, have a daily maximum over 60% around midday.

Therefore, those days are advantageous for electric energy production when the daily course of hourly average wind speed cubes is simple one with only a single maximum. The days when the second wave is random are certainly such ones, as it follows from the above discussion. Assuming a 0.17 significance level, the frequency of advantageous days is between approximately 43% and 70% in all seven stations. Kékestető has the most of them with Keszthely, Budapest Debrecen, Szombathely, Szeged and Pécs following in order. We has not yet discussed the cases when the daily wave dominates and is accompanied by random 12 h wave, i.e., $A_1/E>1.5$ and $A_2/E<1.5$. The number of those is expected to be relatively great. Their proportion (to the number of all the months) by station types is 63.6% in lowland stations, 58.3% in non-lowland stations without Kékestető and 60.4% with it, while 61.8% in all seven stations together. Their monthly distribution is shown in Fig. 8.

The 12-h wave shows most suddenness in the early spring and summer months according to Fig. 8 and it is also these months when the reality of wave 1 increases with the suddenness of the second one according to Table 3 (at 0.17 significance level). We may, with great certainty, expect that daily variation of wind energy will follow the pattern favourable for system management as in Fig. 7.

The most favourable days for the system administrations are very likely those when there is no significant daily variation. Following from the above, the number of such days must be relatively small. The number of months where the daily average wind power

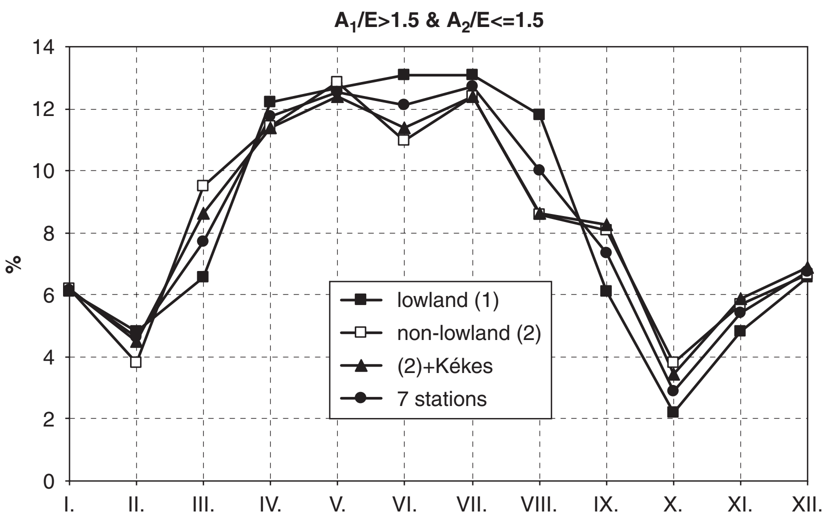


Fig. 8. Combined frequency of the reality of the daily wave and the randomness of the 12 h wave ($p = 0.17$).

shows neither the daily nor the 12 h cycle is altogether 17 in the period discussed here, i.e., only 2%.

As it was already mentioned, the Schuster criterion requires the $A_k/E>3$ condition to be met, which seems to be too strict in case of meteorological and climatological studies [6]. Table 3 contains the frequency of that condition met in case of the daily wave. Even this wave meets that strict condition (at the significance level of 0.01) only in 45.8–74.2% of the cases, contrary to the expectations. The reason for that might be the second less reliable, more random wave, which ‘‘corrupts’’ the simple daily cycle with a midnight minimum and midday maximum. Fig. 9 shows the frequency in percentage by station groups and for all stations together when the $A_1/E>3$ condition is met. The annual course is the most marked with salient values in the spring and in June in case of the non-lowland stations without Kékestető. The tendency remains the same when Kékestető is included. It is still there, although somewhat dampened when all the seven stations are treated together. Lowland stations display a more leveled annual course with a moderate summer maximum.

When the $A_1/E>3$ condition is met, we expect the prevalence of wave 1, since the second wave cannot then influence the simple daily cycle mentioned above. Exactly that is that happens in 71.6–97.2% of $A_1/E>3$ cases (Szeged 71.6, Pécs 76.6, Debrecen 77.8, Budapest 81.2, Keszthely 82.5, Szombathely 87.7, Kékestető 97.2%) the condition $A_2/E\leqslant 1.5$ is also met.

We may ask whether the above strict condition met in case of wave 1 influences the amount of wind energy. Or in other words, whether months that meet that condition provide more or less energy. Table 4 contains the statistical properties of the definite integral ($T_{ga}=F_2(23)-F_2(0)$) in proportion to wind speeds calculated for every hour in all seven stations for the whole time series and its subsets (months) which meet and does not meet the condition. In case of five stations (Debrecen, Budapest, Pécs, Keszthely and Szombathely) out of seven the average energy of months that meet the condition exceeds the average of the whole time series and months that does not meet the condition. In case of Szeged and Kékestető the month, which does not meet the condition exhibit the highest average energy. Another, but different five stations (Debrecen, Szeged, Budapest, Keszthely and Kékestető) exhibit the highest variation coefficient, the value of near

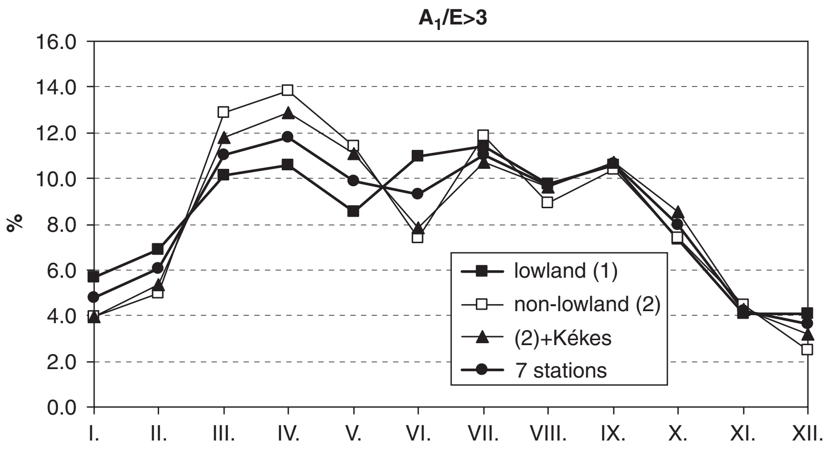


Fig. 9. Monthly frequencies of the reality of the daily wave ($p=0.01$).

Table 4
Statistical properties of the area of the approximation function in proportion to the specific wind power under its curve for the whole time series in months when the conditions $A_1/E>3$ and $A_1/E\leqslant 3$ are met

		Mean	St. dev.	Var. coeff.	Max.	Min.
Debrecen	Whole time	1252.1	619.8	0.50	3810.6	323.5
	$A_1/E>3$	1307.9	664.2	0.51	3810.6	387.8
	$A_1/E\leqslant 3$	1098.6	451.1	0.41	2030.7	323.5
Szeged	Whole time	1741.0	830.3	0.48	5839.1	474.9
	$A_1/E>3$	1717.9	858.5	0.50	5839.1	474.9
	$A_1/E\leqslant 3$	1790.9	774.6	0.43	4693.3	517.4
Budapest	Whole time	907.6	443.4	0.49	3051.9	307.8
	$A_1/E>3$	941.2	488.8	0.52	3051.9	307.8
	$A_1/E\leqslant 3$	851.7	353.1	0.41	1753.6	339.6
Pécs	Whole time	1580.3	895.5	0.57	4702.1	241.5
	$A_1/E>3$	1744.5	964.2	0.55	4265.4	419.6
	$A_1/E\leqslant 3$	1441.4	814.9	0.57	4702.1	241.5
Keszthely	Whole time	830.9	649.1	0.78	3602.7	88.5
	$A_1/E>3$	899.1	736.5	0.82	3602.7	88.5
	$A_1/E\leqslant 3$	741.8	506.0	0.68	2575.4	177.8
Szombathely	whole time	3254.2	2161.0	0.66	11926.3	443.4
	$A_1/E>3$	3443.2	2213.5	0.64	11926.3	443.4
	$A_1/E\leqslant 3$	2890.1	2032.9	0.70	9297.7	656.2
Kékestetö	Whole time	3775.1	2021.5	0.54	10528.3	922.7
	$A_1/E>3$	3606.2	2081.8	0.58	10528.3	922.7
	$A_1/E\leqslant 3$	4088.8	1888.6	0.46	8713.9	1318.1

average deviation independent of the element count, when the strict condition is met, the maximum is in the Kékestető series. Two out of the three daily energy extremes trivially corresponds: these are the maximums for the whole time series in month when the condition is met with the exception of Pécs, and minimums with the exception of Debrecen and Pécs.

The available statistical tests for the hypothesis of sameness of two distributions do not provide reliable results due to the small number of sample elements. But it can be demonstrated that the lognormal distribution fits very good to the empirical distribution of area under the curve (T_{ga}) in all stations. Assuming that this is valid in the case of subsets, also, the question is: can the logarithm of the two subgroups come from the same normal distribution? However, the F test and the two-sample t test furnish an answer for this. Executing these tests we get the results as follows: standard deviations and the expected values are regarded to be the same except Keszthely, where only standard deviations differ from each other significantly. Assuming that these are valid for the non-transformed data, as well, we can establish that monthly mean wind energy is not influenced by the daily course (i.e., daily number of extremities).

3. Conclusions

It can be shown by the help of fitting trigonometric polynomials that the hourly average of cubes of wind speeds, hence the hourly average specific wind power follows one of three possible daily patterns. A single daily maximal and minimal value occur in the first case,

while two daily maximums and minimums in the second one. The third case exhibits no actual daily pattern, but the hourly values show only random alternation. Seasonal distribution of the above cases may provide useful information for energetic systems management when wind power is used to produce electricity. But monthly mean wind energy is not influenced by the daily course (i.e., daily number of extremities).

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